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Advancements in Using Deep Learning Methods for GPR Detection of Tree Roots

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***Abstract*— In recent years, the effects of emerging diseases have caused significant worries among environmentalists and communities, requiring putting efforts into the monitoring and management of natural resources. In this regard, tree roots are one of the most vital and fragile organs of the tree, as well as one of the most complex to investigate. In this way, non-destructive testing (NDT) methods have become one of the most popular techniques for assessing and monitoring tree roots, as opposed to conventional destructive techniques. In this context, ground penetrating radar (GPR) applications have proved to be precise and effective for investigating and mapping tree roots. The inhomogeneity of the soil, however, is a significant obstacle towards the GPR identification of tree roots, and a deep learning (DL)-based method has been recently proposed to tackle this issue. This research, therefore, aims to improve upon the above-mentioned approach, by customising two convolutional neural networks (CNN) methods for the analysis of GPR spectrograms. In this study, the GPR signal is first processed in both the temporal and frequency domains to filter out noise-related information, and subsequently spectrograms are generated. Afterwards, two specifically modified CNN classifiers are implemented and then compared to other DL methods, already validated for tree roots detection. The findings of this study further support the viability of the suggested methodology and open the way for the application of new approaches for evaluating tree root systems.**

***Keywords*—Ground penetrating radar (GPR), tree roots assessment, deep learning, convolutional neural networks, spectrograms**

I. INTRODUCTION

Life on Earth depends heavily on the welfare of trees and forest ecosystems. Oxygen generation, carbon retention, soil stability, food production, and wildlife habitat are merely a few of the numerous benefits of the world's natural heritage. In addition, the benefits of trees on human health and behaviour are supported by scientific evidence, as they contribute to lowering noise and pollution and promoting social contact [1].

Roots are more important than any other organ to the survival of plants and trees. They absorb soil minerals and water, store nutrients, and synthesise hormones, serving as the tree's anchoring and support [2]. The spatial growth of tree roots follows stochastic patterns that might vary considerably among tree species. Moreover, since root conditions typically relate to a tree's health status, their evaluation has been widely utilised as a diagnostic tool in arboriculture applications [3].

Numerous destructive and non-destructive testing (NDT) methods have been employed to efficiently map a tree's root system. Excavation, uprooting, and profile wall techniques all belong to the group of destructive procedures [4]. Nevertheless, in addition to being ineffective and unsuited for large-scale forestry applications, these practices are usually not supported by stakeholders as they might cause irreversible environmental harm [5]. In contrast, NDT methods are able to map root patterns without damaging the tree or interfering with the host material. Numerous NDT techniques, including X-ray tomography, nuclear methods, magnetic resonance, electrical resistivity tomography, and acoustic techniques, have so far been tested for root mapping [4]. Among these, Ground Penetrating Radar (GPR) is an NDT method with numerous applications, ranging from civil and environmental engineering to archaeology and landmine detection. Due to its ease of use, versatility, and high resolution, GPR has demonstrated to be a convenient alternative to both conventional investigation methods and other NDT methods in forestry applications [4]. Therefore, as a non-destructive method for determining root patterns, GPR is rising in prominence. Recent research has focused on the development of automated methods for root mapping in a three-dimensional environment and the analysis of root mass density [6]. In addition, a recent experimental investigation examined the viability of a novel tree root evaluation approach based on the analysis of GPR data in the time and frequency domains [7].

The variability of the soils in which tree roots are buried is one of the greatest challenges when conducting GPR investigations. The combination of soils with varying dielectric characteristics and the presence of other buried items, such as boulders, increase the difficulty of GPR signal processing.

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Within this context, the use of machine learning (ML) and deep learning (DL) approaches was recently tested in this research area, aimed at improving the detection of tree roots in natural soils [8]. In particular, in [8] the DL methods proved to be more effective in performing the task of root detection, showing better performance than conventional ML methods.

II. Aim & Objectives

This research aims to improve upon the latest developments in DL image-based detection and classification methods for the detection of tree roots in natural heterogeneous soils.

The objectives of this research are (*i*) to produce spectrograms (i.e., a 2D graphic representation of a signal's frequency spectrum changing over time) from the GPR signal; (*ii*) to assess the spectrograms using two innovative DL methods, namely AlexNet and GoogleNet, (*iii*) to compare the performance of these convolutional neural networks (CNNs) with the DL methods in [8] to evaluate if the assessment of tree roots may be enhanced further.

III. Methodology

A. GPR Test Site and Equipment

As part of a comprehensive study [6], the GPR survey was conducted at Gunnersbury Park, Ealing, London (United Kingdom). A total of 36 semi-circular scans were conducted around the tree under investigation. The initial survey transect was positioned 0.50 metres from the bark, whereas the distance between scan lines was 0.30 metres. (Fig.1).

An Opera Duo ground-coupled GPR system manufactured by IDS GeoRadar (Part of Hexagon) and equipped with 700 MHz and 250 MHz central frequency antennas was used for survey purposes. A time window of 80 ns, discretised across 512 samples, was used for data collection. The horizontal resolution was set to 3.06 10^{-2} m. Data analysis was limited to the 700 MHz antenna output, to maximise the resolution.

Fig. 1. The investigated area

Subsequently, the dataset was validated by carrying out a controlled excavation of 16 m^2 within the investigated area, the position of which was determined based on the GPR investigation's coordinates. To this end, the root system was exposed by excavating the soil in layers of 0.10 m at a time.

B. Data Processing Methodology

1) GPR Signal Processing

This phase aims to reduce noise-related characteristics in the GPR data to provide quantifiable information and easily interpretable images for further results analysis. Therefore, data are processed via a multi-stage approach that includes filters acting in both the temporal and frequency domains, i.e. zero-offset removal, time-zero correction, time-varying gain, singular value decomposition filter (SVD), and band pass filter [7].

Subsequently, spectrograms of the GPR signal (Fig. 2) are created by applying the Short-Time Fourier Transform (STFT) as follows:

$$STFT\ (t\ ,\ \omega) = \int_t [x(t) \cdot w(\tau - t)] \cdot e^{-j\omega t}\, dt \qquad (1)$$

where STFT is the frequency energy at time t and frequency ω, x is the reflected amplitude and w is the window function [7].

2) Data Categorisation

In order to train the DL algorithms, the image database must be categorised so that classifiers can reliably recognise and differentiate between features from diverse targets. This research employs four categories to categorise the characteristics uncovered during the field investigations:

- Roots
- Root clusters
- Stones
- No target

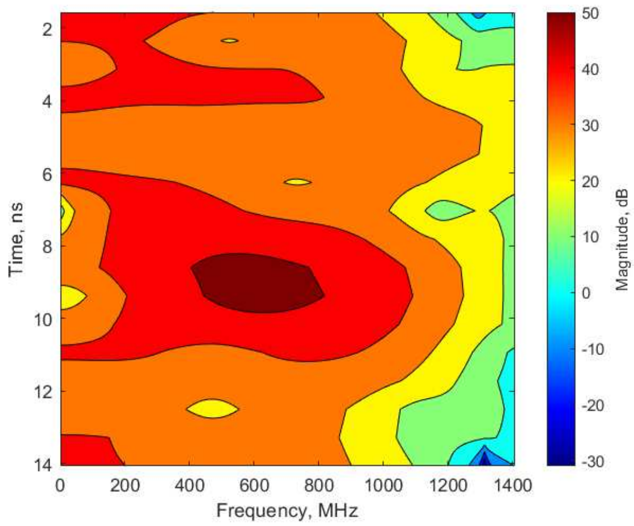

Fig. 2. Spectrogram of the GPR signal

Furthermore, to increase the amount of data and the efficiency of the investigated classifiers, the spectrograms are corrupted with Gaussian noise, with a noise variance of 0.1, 0.5 and 1.

3) CNN-based Detection Methods

To discriminate between the presence or absence of roots or other buried targets in heterogeneous soils, two CNN models have been adapted to the scenario of tree roots detection:

- AlexNet: a CNN architecture with five layers with a combination of max pooling, followed by three fully connected layers [9]. The use of rectified linear units diminishes the computation times, especially during network training, while mitigating the problem of vanishing gradients.
- GoogLeNet: a CNN developed by Google that is 22 layers deep [9]. It was created with the aim of addressing the problem of overfitting by having multidimensional filters operating on the same level.

The results obtained from the above CNN methods were subsequently compared to the results of the following image-based DL methods, as described in [8]:

- SqueezeNet [10]: a small network with an architecture of 18 layers. Having a small number of parameters, it needs less computational effort, memory requirements and running time.
- VGG-16 [11]: a 16 layers deep CNN with an extensive network of about 138 million parameters. While requiring a considerable amount of time to train, VGG-16's straightforward and uniform architecture makes it an attractive option.

IV. Main Results and Short Discussion

The proposed CNN classifiers are compared with the image-based DL classifiers described in [8] to assess their accuracy in tree roots detection. Fig. 3 illustrates the overall performance of each analysed method as the Gaussian noise variance changes from 0.1 to 1.

For noise variance of 0.1, all the proposed classifiers show a comparable accuracy ranging between 100% - 99%. However, as predicted, the performance of each classifier falls as the noise level rises. For noise variances of 0.5 and 1, the VGG-16 still shows the highest accuracy, ranging between 100% - 96%. Nevertheless, the proposed AlexNet shows comparable and accurate results, with accuracies of 99% and 91% for noise variances of 0.5 and 1, respectively. The proposed GoogLeNet classifier also shows solid results for a noise variance of 0.5, with an accuracy of 97%, which is comparable to the performance of all the investigated classifiers for this noise variance. However, for a noise variance of 1, GoogLeNet performance decreases to 82%, which is less efficient than VGG-16 and AlexNet but significantly more accurate than the SqueezeNet DL classifier with an accuracy of 60%. Consequently, these results clearly show the reliability and efficiency of the proposed CNN detection framework.

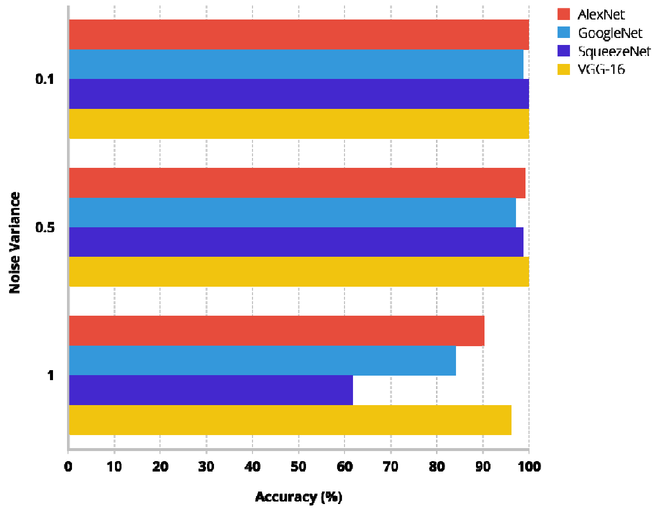

Fig. 3. Performance of the investigated classifiers, for values of Gaussian noise of 0.1, 0.5 and 1

It is worth noting that, especially for the AlexNet model, the achieved results are accurate compared to the VGG-16, which requires considerably higher computation times.

The accuracy of the results is further investigated through the following performance metrics:

- Precision: determines the proportion of positive class forecasts that correspond to the positive class;
- Recall: quantifies the ratio between positive cases and all the cases in the dataset;
- F-measure: assesses the test's accuracy by providing the harmonic mean of precision and recall values.

The values of precision, recall and F-measure for the proposed classifiers are reported in Tables I, II and III, for noise variances of 0.1, 0.5 and 1, respectively. Results confirm that the VGG-16 continue to show the highest levels of accuracy for all the investigated cases. Nevertheless, the proposed AlexNet and GoogLenet CNN classifiers show comparable accuracy to the DL methods for low to medium noise variances, and significantly outperform the SqueezeNet classifier for a noise variance of 1.

V. Conclusion

This study shows the latest developments of a novel approach for the detection of tree roots using ground penetrating radar (GPR). The aim of this investigation is to assess the performance of novel convolutional neural networks (CNN) methods for the analysis of GPR data, as compared to the performance of other deep learning (DL) image-based methods. To this end, a tree root system was investigated using GPR and then partially exposed through excavation for validation purposes. The Short-Time Fourier Transform (STFT) approach was used to transform GPR data into spectrograms, which were then analysed with two ad-hoc modified CNN classifiers (i.e., AlexNet and GoogLeNet).

TABLE I. PERFORMANCE METRICS FOR THE IMAGE-BASED DL CLASSIFIERS AND THE PROPOSED CNN (NOISE VARIANCE 0.1)

	SqueezeNet	VGG-16	AlexNet	GoogLeNet
Precision	1	1	1	0.987
Recall	1	1	1	0.990
F-measure	1	1	1	0.987

TABLE II. PERFORMANCE METRICS FOR THE IMAGE-BASED DL CLASSIFIERS AND THE PROPOSED CNN (NOISE VARIANCE 0.5)

	SqueezeNet	VGG-16	AlexNet	GoogLeNet
Precision	0.987	1	0.992	0.972
Recall	0.990	1	0.992	0.980
F-measure	0.987	1	0.992	0.975

TABLE III. PERFORMANCE METRICS FOR THE IMAGE-BASED DL CLASSIFIERS AND THE PROPOSED CNN (NOISE VARIANCE 1)

	SqueezeNet	VGG-16	AlexNet	GoogLeNet
Precision	0.617	0.962	0.902	0.840
Recall	0.695	0.962	0.935	0.847
F-measure	0.600	0.962	0.910	0.820

The comparison of results obtained with existing DL classifiers demonstrates that, among the proposed CNN architectures, AlexNet is capable of distinguishing tree roots from other buried objects with high precision, without requiring high computational and training times.

This research confirms that the presented approach is appropriate for application in tree monitoring, allowing for the fast and non-invasive assessment of roots. Further research and development are planned to reduce the risk of false positives, thus paving the way for a more systematic monitoring approach with positive implications for trees' conservation and management.

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